

Co-movements in financial fluctuations are anchored to economic fundamentals: A mesoscopic mapping

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Abstract

We demonstrate the existence of an empirical linkage between the nominal financial networks and the underlying economic fundamentals across countries. We construct the nominal return correlation networks from daily data to encapsulate sector-level dynamics and figure the relative importance of the sectors in the nominal network through a measure of centrality and clustering algorithms. The eigenvector centrality robustly identifies the backbone of the minimum spanning tree defined on the return networks as well as the primary cluster in the multidimensional scaling map. We show that the sectors that are relatively large in size, defined with the metrics market capitalization, revenue and number of employees, constitute the core of the return networks, whereas the periphery is mostly populated by relatively smaller sectors. Therefore, sector-level nominal return dynamics is anchored to the real size effect, which ultimately shapes the optimal portfolios for risk management. Our results are reasonably robust across 27 countries of varying degrees of prosperity and across periods of market turbulence (2008-09) as well as relative calmness (2015-16).

1 Introduction

Widespread existence of bubbles in the financial markets and extreme movements of return series indicate that the relationship between the macroeconomic fundamentals and the asset prices is unstable [1]. The ‘excess volatility puzzle’ in the stock markets refers precisely to this disconnect between the volatility of asset returns and the movements of the underlying fundamentals [2]. Recent research emphasizes the roles played by wrong expectation, bounded rationality, herding behavior,

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etc. as being important causal factors for the observed disconnect [3]. In this paper, we present an alternate view that the co-movements in financial assets are anchored to the corresponding macroeconomic fundamentals. Thus, nominal returns from individual assets might drift far from what can be predicted using expected cash-flow, while the joint evolution of the co-movement of returns are still related to aggregate size variables like market capitalization, revenue or number of employees.

In the following, we consider the economy to be a multi-layered network [4] defined over nodes at different levels of granularity, each having significantly different properties. At the micro level, firm size distributions show power law decays [5] and bi-exponential growth size distributions [6]. A scaling relationship between size of the firms and the corresponding volatility was also proposed [6]. At the macro level, similar features are seen, for example, as has been proposed by [7]. These suggest that there might be universal features of growth processes of economic entities (see also [8]). Ref. [7] also argued that the dispersion in relative sizes of firms contribute substantially to the aggregate volatility of an economy, providing a link from the micro level to the macro level. A complementary view has emerged from the network literature that the dynamics at the intermediate sectoral level could play an important role in shaping the aggregate macro-level dynamics [9]. We focus precisely on the ‘mesoscopic’ level, which identifies with the production process of the economy while being granular enough to capture the network structure of co-movements in return fluctuations.

There are two modes of connectedness across sectors. At the nominal pricing level, the fluctuations of returns from the sectoral indices show the degree of co-movements across sectors. At the production level, the flow of goods and services across sectors [10] gives rise to dispersion in relative sizes of these sectors. Here, we show that there exists a universal mapping between the inter-sectoral return dynamics and relative sizes of the sectors defined with multiple metrics, thus highlighting an empirical link between financial networks and macroscopic variables in a granular economy. In particular, we show that the sectors with disproportionate shares of the economy, constitute the core of the corresponding return networks. Therefore, at the ‘mesoscopic’ level, the dispersion in size explains the dispersion in ‘centralities’ of nominal fluctuations of sectors.

To study the topology of the return network, we construct return correlation matrices from sectoral indices for 27 countries, and apply two commonly used clustering algorithms (minimum spanning tree and multi-dimensional scaling) to group sectors based on their co-movements. The influence of the sectors in the whole network can be found by using the eigenvector centrality, which is able to handle both directed as well as weighted graphs [11]. In this paper, we also propose a methodology to find a binary characterization of the ‘core-periphery’ structure by using a modification of the eigenvector centrality. Such classification of the sectors according to whether they belong to the core or the periphery, allows one to pin down exactly which sectors are driving the market correlations. We show that these sectors identified as core by the centrality measure, also constitute the backbone of the minimum spanning tree (MST) and cluster very closely in multi-dimensional scaling (MDS) maps, thereby confirming the robustness of our method of extraction of the core-periphery structure.

To study the connection between the financial network with the underlying production process,

we regress the eigenvector centrality measure on sector sizes defined with three different metrics, viz., market capitalization, revenue and employment, all aggregated at the sectoral level. The results across 27 countries clearly indicate that the dispersion in the economic size explains the variation in the dispersion of sectoral centralities in the correlation matrix. This is the primary finding of our paper, as it establishes the linkage between the economic fundamentals and the fluctuations of the return series. Finally, we study the risk diversification of a portfolio comprising sectoral indices, based on the eigenvector centralities. For the sake of simplicity, we use a rudimentary Markowitz portfolio allocation problem and show that the core sectors, i.e., the ones with sufficiently high centralities, do not usually appear in a minimum variance portfolio. Intuitively, very large sectors contribute significantly to the movement of the return correlations and they constitute the ‘market factor’ of correlations. Hence, for reduction of the volatility of the portfolio, the weights assigned to such sectors contributing to the aggregate risk, are necessarily minimized.

We perform statistical tests on a comprehensive list of 27 countries that includes developed as well as developing countries across five continents, totaling 72 sectors in the financial economies. We base most of our studies on a recent and relatively calm period (2015-16), and then compare and contrast with a volatile period (2008-09), in order to check robustness of our findings across time. We show that the 2015-16 period gives very consistent results (25 out of 27 countries are in expected direction), whereas 2008-09 period is largely consistent (22 out of 26), although there are some aberrations as the number of statistically insignificant relationships increases. A consistent pathogenic case is Greece, which has been known to possess weak economic fundamentals along with severe crises in the financial markets in the recent times.

2 Data, Definitions and Methods

2.1 Data Description

We have used the sectoral price indices from the Thomson Reuters Eikon database [12], within the time frames January 2008- December 2009, and October 2014- September 2016. We have analyzed the data for a total of 72 sectors (see table 1), for the following countries: (1) **AUS**- Australia (2) **BEL**- Belgium (3) **CAN**- Canada (4) **CHE**- Switzerland (5) **DEU**- Germany (6) **DNK**- Denmark (7) **ESP**- Spain (8) **FIN**- Finland (9) **FRA**- France (10) **GBR**- United Kingdom (11) **GRC**- Greece (12) **HKG**- Hong Kong (13) **IDN**- Indonesia (14) **IND**- India (15) **JPN**- Japan (16) **LKA**- Sri Lanka (17) **MYS**- Malaysia (18) **NLD**- the Netherlands (19) **NOR**- Norway (20) **PHL**- Philippines (21) **PRT**- Portugal (22) **QAT**- Qatar (23) **SAU**- Saudi Arabia (24) **SWE**- Sweden (25) **THA**- Thailand (26) **USA**- United States of America and (27) **ZAF**- South Africa, spread across the continents of the Americas, Europe, Africa, Asia and Australia. The time series data on the real variables, such as market capitalization, revenue and the number of employees within each sector, are also available in the same database although at the company level rather than at the sectoral level. Hence, for our purposes of constructing sector-level macro aggregate variables, we collected the companies listed within each sector for one particular country, and then aggregated

the relevant company-specific variables across all such companies within the corresponding sector.

We find that the USA economy is a good representative of the empirical results and hence, in the main text, we present the results for the USA economy in details. For the other 26 countries, the detailed results are presented in the Supplementary material. Note that data for Finland (FIN) was not available for the period 2008-09.

Table 1: Abbreviations of the 72 sectors analyzed.

Label	Sector	Label	Sector
AF	Agro & Food Industry	MD	Media
AG	Agriculture	MF	Manufacturing
AM	Automobiles	MG	Mining
BC	Building & Construction	MI	Multi Investments
BF	Banks & Finance	MID	Miscellaneous Industries
BFT	Beverage, Food & Tobacco	MM	Metals & Mining
BK	Bank	MO	Mining & Oil
BM	Basic Materials	MOT	Motors
BR	Basic Resources	MP	Metal Products
CC	Consumer & Cyclical	MP1	Media & Publishing
CD	Consumer Discretionary	MT	Media & Telecomm
CD1	Consumer Durables	OC	Oil & Coal Products
CE	Cement	OG	Oil and Gas
CG	Consumer Goods	PC	Property & Construction
CG1	Capital Goods	PE	Power & Energy
IT	Information Technology	PG	Personal Goods
CH	Chemicals	PH	PetroChemicals
CM	Consturction & Materials	PL	Plantation
CN	Construction	PR	Property
CP	Consumer Products	PSU	Public Sector Undertaking
CS	Consumer Staples	RB	Rubber
CSR	Consumer Services	RE	Real Estate
EC	Energy & Chemical	RT	Retail
EG	Energy	RY	Realty
EM	Electrical Machinery	SC	Semiconductor
EU	Energy & Utilities	ST	Steel
FB	Food & Beverages	SU	Securities
FN	Finance	TC	Telecom
GD	Gold	TD	Trade
HC	Health Care	TE	Transport & Equipment
HG	Household Goods	TP	Transport
HT	Hotel & Tourism	TS	Trade & Services
ID	Industries	TT	Travel & Tourism
IF	Infrastructure	TX	Textiles
IP	Industrial Production	UT	Utilities
IS	Insurance	WS	Wholesale

2.2 Correlation coefficient and the distance metric

If $r_{1...N}$ represents the return of N sectors, which is calculated as $r_i(\tau) = \ln P_i(\tau) - \ln P_i(\tau - 1)$, where $P_i(\tau)$ is the adjusted closure price of sector i in day τ , then the equal time Pearson correlation coefficients between sectors i and j is defined as

$$\rho_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{[\langle r_i^2 \rangle - \langle r_i \rangle^2][\langle r_j^2 \rangle - \langle r_j \rangle^2]}}, \quad (1)$$

where $\langle \dots \rangle$ represents the expectation. We use $\boldsymbol{\rho}$ to denote the return correlation matrix.

Following a standard procedure in the literature, we construct the distance metrix from the correlation coefficients using the following transformation, $d_{ij} = \sqrt{2(1 - \rho_{ij})}$, where $2 \geq d_{ij} \geq 0$.

All elements of the matrix d_{ij} are “ultrametric” [13, 14, 15]).

2.3 Eigenvector centrality

To analyze the influence of a sector in the whole network, the ranking of the sectors is measured by the eigenvector centrality. It is not necessary that a sector with high eigenvector centrality is highly linked but the sector might have few but important links. Given an $N \times N$ matrix \mathbf{A} , the eigenvector centrality is defined as an $N \times 1$ vector \mathbf{x} , which solves

$$\mathbf{A}\mathbf{x} = \lambda_m\mathbf{x}, \quad (2)$$

where λ_m is the dominant eigenvalue of \mathbf{A} .

In general, almost all pair-wise correlations are positive. However, in rare cases (e.g., Gold sector in Canada), certain sectors show mild negative correlations with other sectors. We consider the absolute value of the correlation matrix $|\rho|$ for computing the eigenvector centrality, since according to the Perron-Frobenius theorem, a real square matrix with positive entries has a unique largest real eigenvalue and the corresponding eigenvector has strictly positive components. Finally, we normalize the centrality vector \mathbf{x} such that $\sum_i x_i = 1$.

We consider a further modification of the centrality measure to identify the core-periphery structure in a binary fashion. Instead of the level values of the correlation coefficients, we consider ρ^c , where c is a sufficiently large *even* number, since this transformation would make the many weak correlations have asymptotically zero weights while maintaining positive signs. We found that $c = 2^5 = 32$ is the lowest value, which gives reasonably good estimates of the backbone of the minimum spanning tree. Hence, we present results for $c = 32$ although, in principle, one can use higher values as well. To determine the core sectors of a country, we then construct a threshold value θ_e , as a fixed percentage of the coefficient of variation (standard deviation/mean) for the eigenvector centralities. If the sectoral centrality is above the threshold value θ_e , then the sector is considered as core, otherwise not.

2.4 Multidimensional scaling

To analyze the similarity among different sectors in terms of distances (d_{ij}), geometrical maps are generated using MDS for each of 27 countries, where each sector corresponds to a set of coordinates in a multi-dimensional space. The concept behind MDS is to represent two similar sectors as two sets of coordinates that are close to each other, and two sectors behaving differently are placed far apart in the space [16]. Given d_{ij} , the aim of MDS is to generate N vectors $y_1, \dots, y_N \in \mathbb{R}^q$, such that

$$\|y_i - y_j\| \approx d_{ij} \quad \forall i, j \in N, \quad (3)$$

where $\|\cdot\|$ represents vector norm. To plot the vectors y_i in the form of a map, the embedding dimension q is chosen as 2. Generally, MDS can be obtained through an optimization problem, where (y_1, \dots, y_N) is the solution of the problem of minimization of a cost function, such as

$$\min_{y_1, \dots, y_N} \sum_{i < j} (\|y_i - y_j\| - d_{ij})^q. \quad (4)$$

2.5 Minimum spanning tree (MST)

MST is a clustering algorithm. By giving distance matrix d_{ij} as input, MSTs are constructed for N sectors for each of the 27 countries, which are connected, undirected graphs such that all the N sectors are connected together with the minimal total weighting for its $N - 1$ edges, i.e., the total distance is minimum.

2.6 Linear regression

For relating the size with the variation of centrality, we employ the standard econometric technique of ordinary least squares. Let us assume that the model to explain x_i data-points, for $i = 1, \dots, N$, is given by the following

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad (5)$$

where x is the explanatory variable, y is the dependent variable and ϵ denotes error terms. The ordinary least squares method minimizes the sum of the squared errors, to estimate the coefficients β . Throughout our regression analyses, we have used scaled variables: $[\text{variable-mean}(\text{variable})]/\text{standard deviation}(\text{variable})$. We carried out the estimation exercise using the MATLAB and R software packages.

3 Results

In this section, we describe the three main results. Firstly, the return correlation network closely mimics the actual production network and so the core-periphery structure of the return correlation network is closely associated with the relative sizes of the sectors. Secondly, based on the findings for two periods of the empirical data (calm and volatile periods), our results are robust and hence universal, with respect to time. Finally, the core sectors which are typically very large in size, drives the market mode of the returns and hence, is riskier than the peripheral sectors as observed in minimum variance portfolio management.

3.1 Financial fluctuations and economic fundamentals

Given the return correlation ρ , we computed the modified eigenvector centralities to find the core sectors of the countries, and to visualize the co-movements and clusters of sectors based on return

correlations, we applied two clustering algorithms, viz., MDS and MST. Fig. 1 (*Upper*) shows the MST. Fig. 1 (*Upper Left Inset*) shows that using the eigenvector centrality, we can identify that out of 10 sectors of the USA, 5 sectors constitute the core of the economy, viz., Finance (FN), Information Technology (IT), Industries (ID), Basic Materials (BM) and Consumer Discretionaries (CD) (see table 1 in Sec. 2.1 for names of the sectors). Fig. 1 (*Lower Right Inset*) shows the MDS. The MST generates a core-periphery structure based on minimizing the distance between correlated sectors, and since it is a hierarchical clustering method, similar sectors can be found close to each other (or in one branch). Similarly, closer the sectors are placed on the MDS map, more correlated (similar) they are; farther they are placed on the map, less correlated they are.

There are two major observations: First, the MST shows that all core sectors form a chain or the “backbone” in the tree (see Fig. 1 (*Upper*)). Similarly, the MDS also reiterates the same information: the core sectors, as identified by the modified eigenvectors centrality, belong to one cluster in the MDS (see Fig. 1 (*Lower Right Inset*)); all sectors with negligible centrality are spaced in the periphery – far away from the core – in the MDS. Thus, our method of the modified centrality to extract the core sectors is reinforced by the clustering algorithms, indicating the robustness of our findings. Second, the MST built from the return correlation matrix, contains information about the actual production structure of the economy. For example, Energy (EG) is most closely related to Basic Materials (BM), which in turn is related to Industries (ID), and so on. On the other end of the MST, Consumer Staples (CS) is connected to Telecom (TC) sector, Utilities (UT) and Consumer Discretionary (CD). Again, this qualitative feature is quite robust, as observed in almost all the countries analyzed.

More importantly, we show that the core-periphery structure based on the return correlation matrix, ρ , has an intriguing relationship with the relative sizes of the sectors. In order to demonstrate and establish the relationship, we study the variations in the eigenvector centralities of the return correlation matrix, and exploit the variations in three major variables, viz., aggregate market capitalization, aggregate revenue and the aggregate employment. We have described in Sec. 2.1 how we constructed the sector-level data by aggregating the company-level data. In Fig. 1 (*Lower*), we plot the linear regressions of scaled eigenvector centrality with the (scaled) market cap, revenue and employees for the USA. We have performed similar analyses for the other countries, and tabulated the results in the Supplementary material. Detailed analyses and tables suggest that generally, such a mapping exists for almost all countries.

Fig. 2 shows the core-periphery structure for all countries. As can be seen, there are at least two sectors in the core for all countries, but the core-periphery structure often changes with time (when compared for the periods 2008-09 and 2015-16). Thus, the relative importance of the sectors does change with time, and the sectoral dynamics and co-movements may convey deeper insight about the aggregate macro-level dynamics. In Fig. 3, we present similar MSTs (with the core/backbone colored in red) for 20 other countries, elucidating the core-periphery structures.

Fig. 4 shows the results of regressing the sectoral eigenvector centralities on the sector-level aggregate market capitalization, revenue, and employees, for the years 2008-09 and 2015-16. As

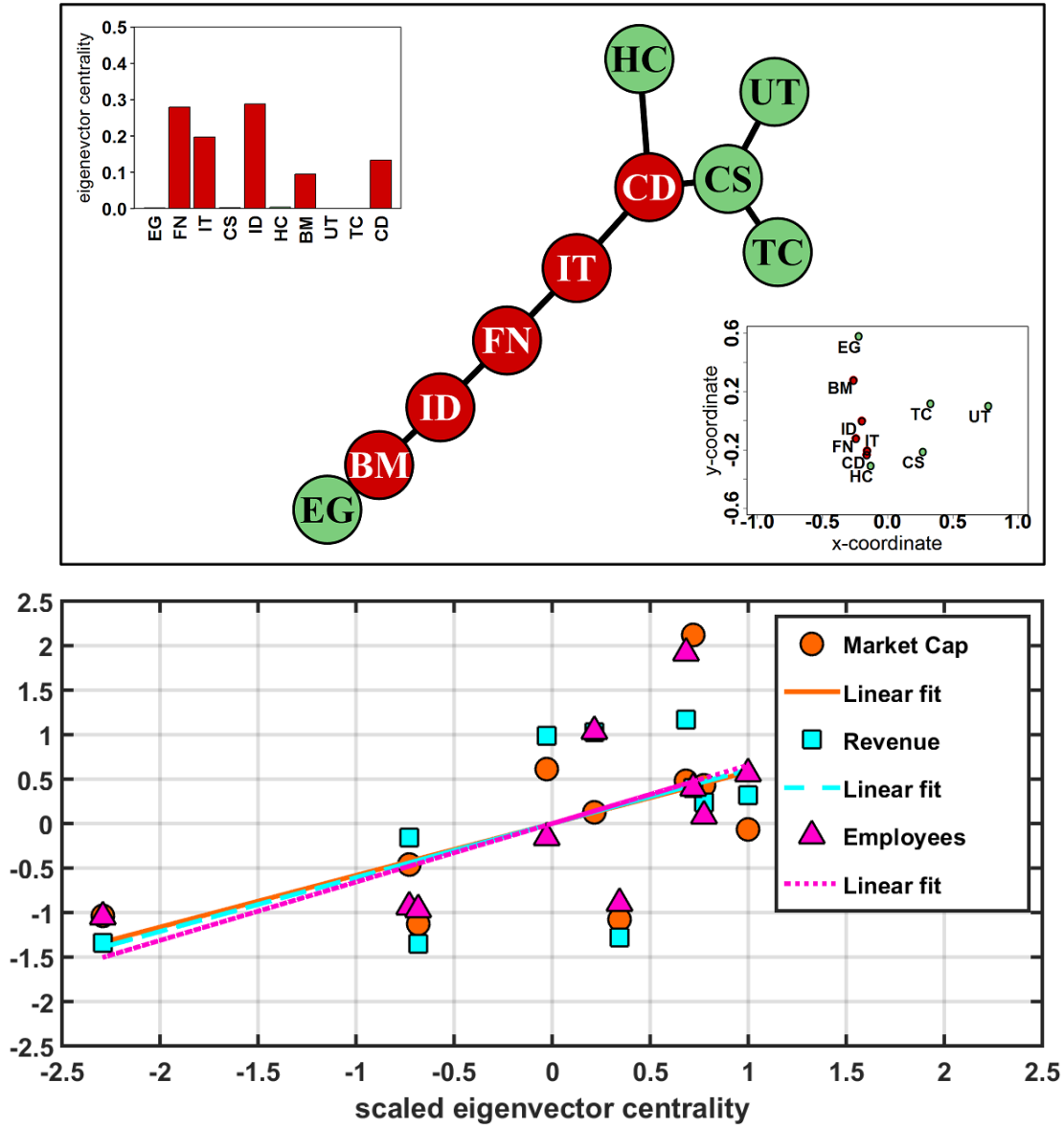


Figure 1: (Color online) Results for USA: (*Upper*) Identification of the sectors that are in the core (red) and periphery (pale green) of the minimum spanning tree, where the nodes represent different sectors; sectoral abbreviations given in the table 1. *Top Left Inset*: Eigenvector centralities of ρ^{32} . *Lower Right Inset*: Multidimensional scaling, where the different sectors are plotted as coordinates in a map. (*Lower*): Linear regressions of scaled eigenvector centrality with scaled market capitalization (orange filled circles), scaled revenue (cyan filled squares), and scaled number of employees (magenta filled up-triangles). The best fits (linear regressions) are plotted as lines for market capitalization (orange solid), revenue (cyan long dashed) and employees (magenta short dashed). The variables have been scaled so that they can be plotted and compared in the same figure.

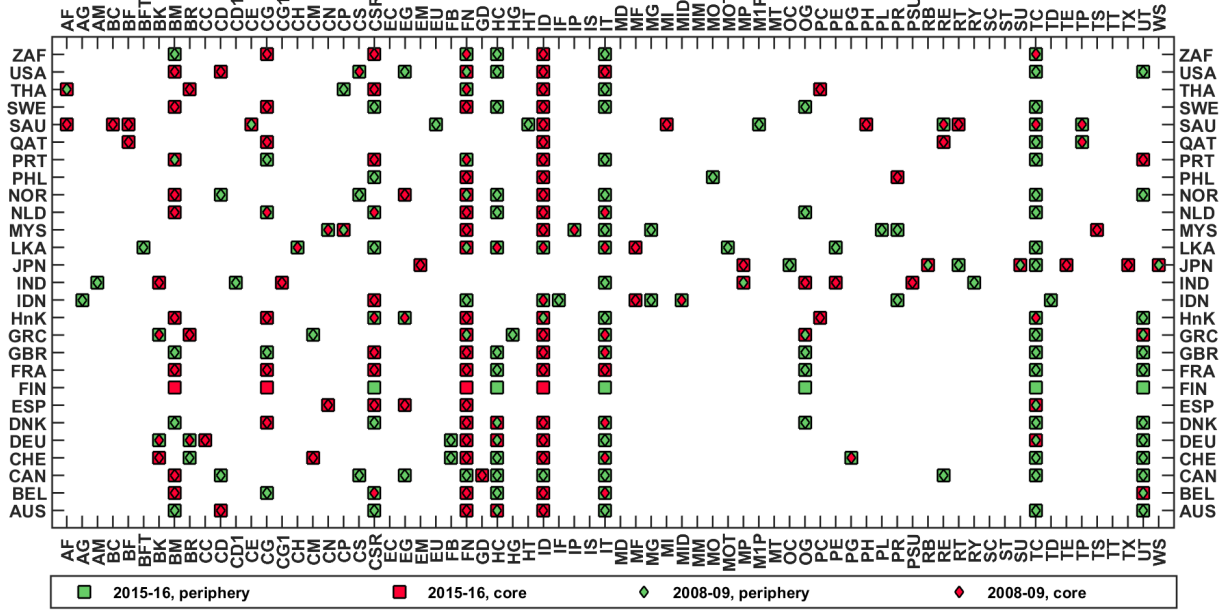


Figure 2: (Color online) Sectoral dynamics and core-periphery structure: Chart of the 72 sectors (horizontal axis) in the 27 countries (vertical axis), showing the core (red) and periphery (pale-green) structures for the years 2008-09 (diamonds) and 2015-16 (squares), and their changes over time. The sector abbreviations can be found in the table 1 in Sec. 2.1. Visual inspection reveals that sectors FN and ID are frequently occurring in the core/backbone, across almost all countries.

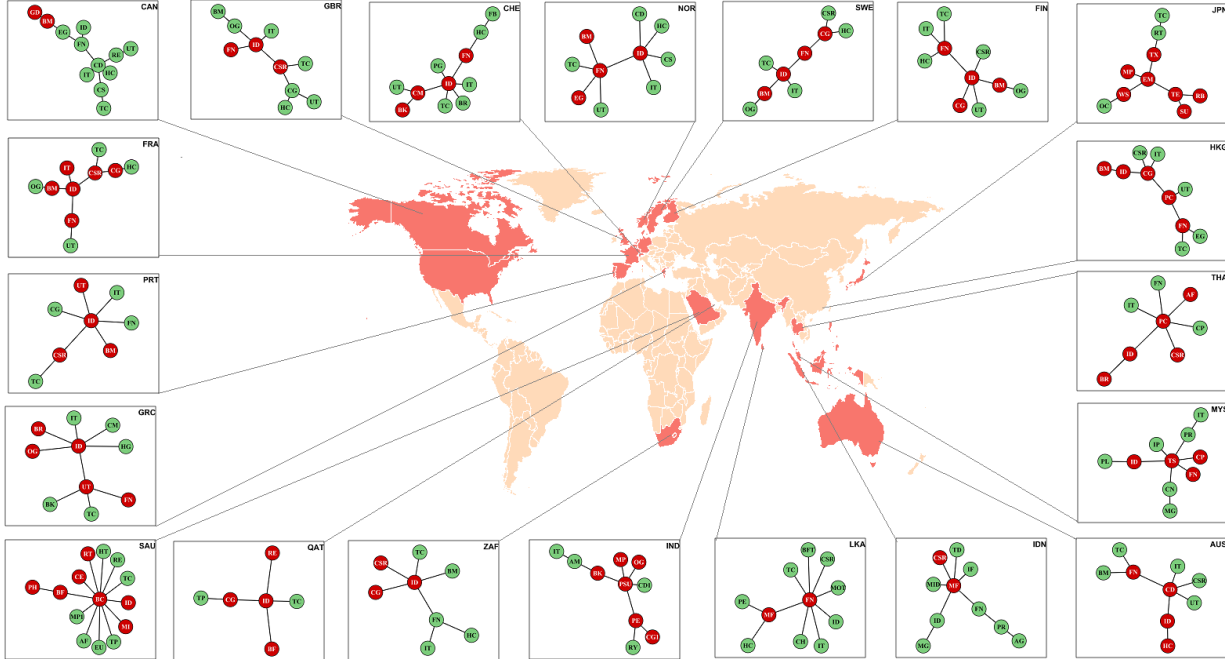


Figure 3: (Color online) Minimum spanning trees for 20 countries out of the 27 countries (shown in peach) that are being studied across the globe. The core sectors are colored red (darker shade), while the sectors in the periphery are in pale green (lighter shade). The sector abbreviations can be found in the table 1 in Sec. 2.1.

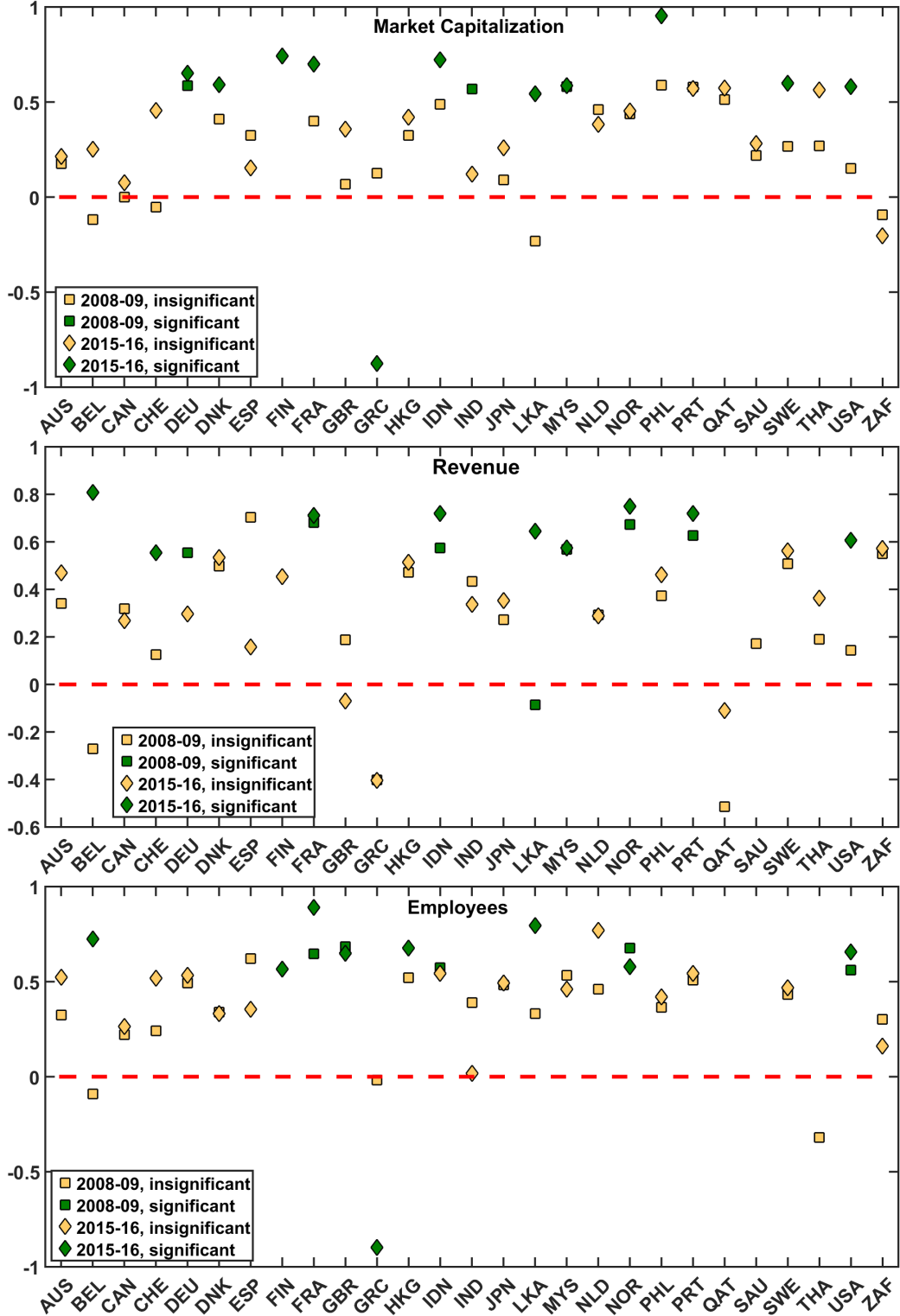


Figure 4: (Color online) Comparison of the regression results (estimates of β_1 using Eq. 5) to explain variation in the sectoral eigenvector centralities (y) by the variation in sector-level macro data (x). *Upper*: market capitalization, *Middle*: Revenue, *Lower*: Employees, for the years 2008-09 and 2015-16. Detailed estimation results are given in the tables in Supplementary material.

we see in Fig. 4 (*Upper*), for 2015-16, the coefficient β_1 for market capitalization 25 out of 27 countries are positive, and 11 out of those 27 countries have statistically significant relationships. The two countries which have very mildly negative relationships, are Greece (significant) and South Africa (insignificant). For 2008-09, the coefficient β_1 for 22 out of 26 countries are positive, and 3 out of those 26 countries have statistically significant relationships. Also, the countries Belgium, Switzerland, South Africa and Sri Lanka have negative relationships. In Fig. 4 (*Middle*), for 2015-16, the coefficient β_1 for revenue, 23 out of 26 countries are positive, and 9 out of those 26 countries have statistically significant relationships. The three countries which have negative (and statistically insignificant) relationships, are Greece, Qatar and United Kingdom. For 2008-09, the coefficient β_1 for 22 out of 26 countries are positive, and 9 out of those 24 countries have statistically significant relationships. Finally, in Fig. 4 (*Lower*), for 2015-16, the coefficient β_1 for employees, 23 out of 24 countries are positive, and 9 out of those 24 countries have statistically significant relationships. The only country which has negative (and statistically significant) relationship, is Greece. For 2008-09, the coefficient β_1 for 21 out of 24 countries are positive, and 5 out of those 24 countries have statistically significant relationships. For detailed statistical values of regressions performed on the sector-level aggregate data, please refer to the text in Supplementary material.

There is already an existing finding that centralities in input-output networks are closely related to the relative sizes of the corresponding nodes (see Ref. [9]). However, here we further show that the centralities based on nominal return fluctuations are related to relative size, i.e., the return network is also very closely related to the underlying size effects. An immediate corollary is that the core sectors of the return correlation network are also economically big, and hence, the market effect of the correlations are driven by the sectors, which have very high market capitalization (or other indicators like revenue and employment).

3.2 Robustness: volatile period versus calm period

We studied the dynamics of a total of 72 sectors across 27 countries, covering both developed and developing economies. Using methods of modified eigenvector centrality, MDS and MST, we can find the core-periphery structure of all the economies. Fig. 2 showed the core-periphery structure of all the countries, and indicated that most of the sectors do not change much in the core-periphery structure during the periods of market turbulence, as well as relative calmness. There are of course, some sectors who were core in a volatile period, became the peripheral ones in the calm period, and vice versa. Fig. 5 shows the comparison among the modified eigenvector centralities for the years 2008-09 and 2015-16, for the four countries: United Kingdom, India, Japan, and United States of America, as examples. The relative importance of each sector can be compared for the volatile and calm period. Certainly the sectoral dynamics are interesting to note in the different countries, and may help in taking important policy decisions in economic growth and development.

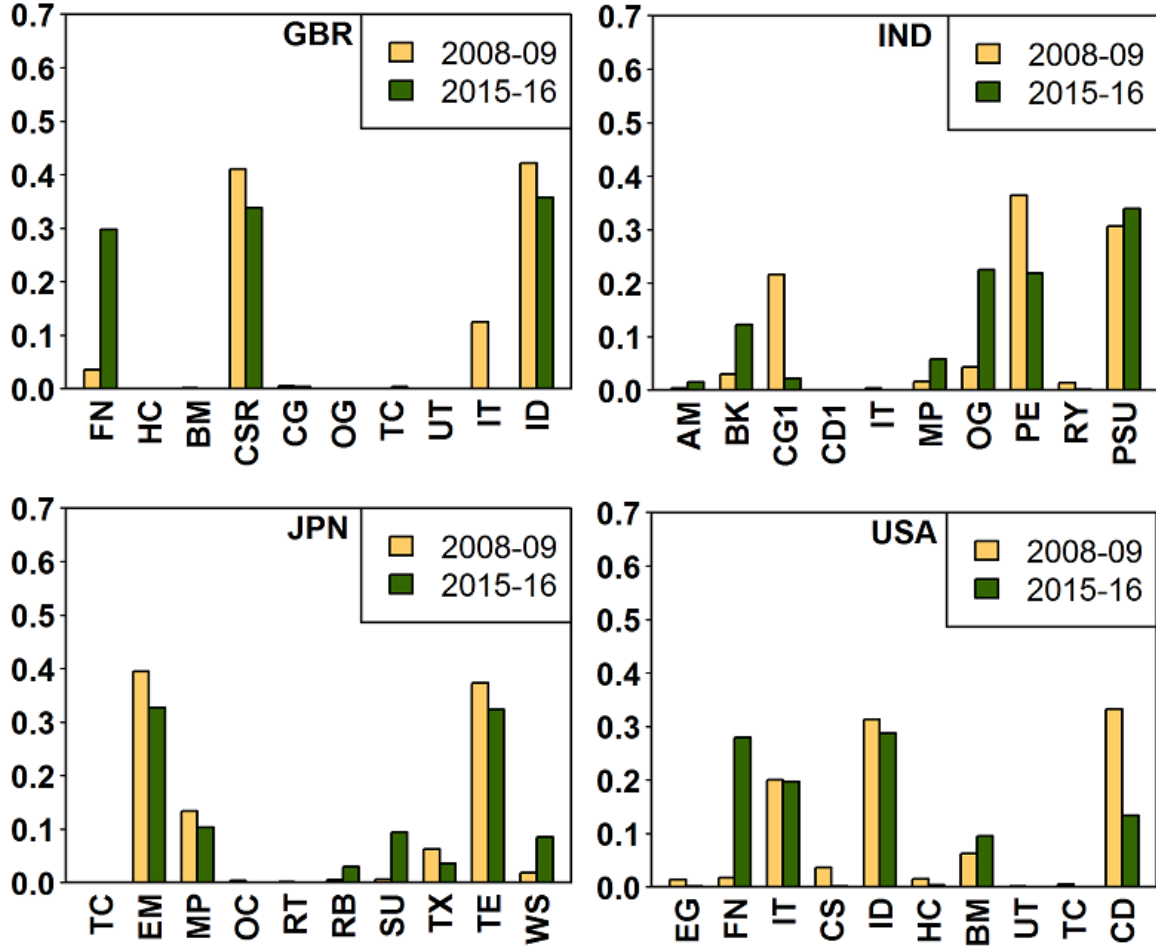


Figure 5: (Color online) Sectoral dynamics and robustness: The comparison of the eigenvector centralities for the years 2008-09 (light orange) and 2015-16 (dark green) for four countries. *Upper Left*: United Kingdom (GBR), *Upper Right*: India (IND), *Lower Left*: Japan (JPN), *Lower Right*: United States of America (USA).

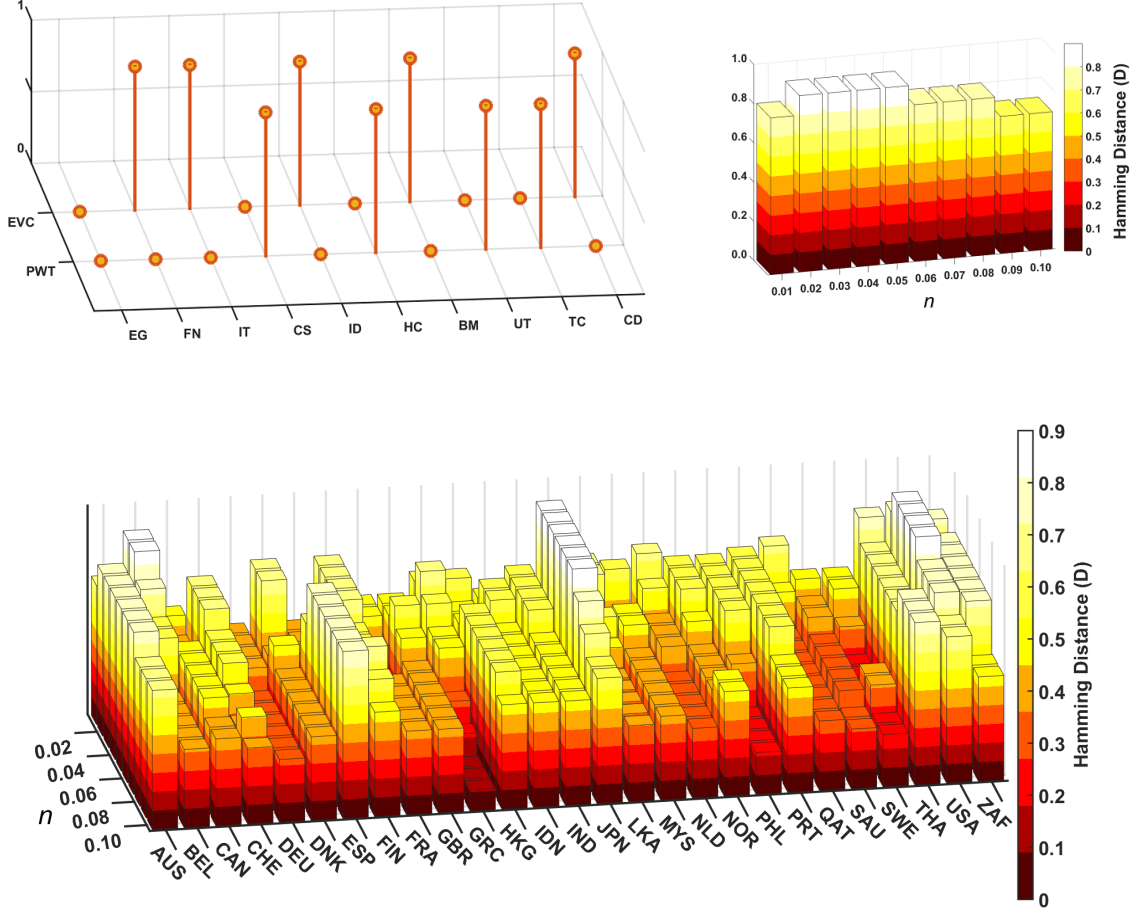


Figure 6: (Color online) *Upper Left*: Relationship between the bit-strings of sectoral centralities (EVC) and their corresponding inclusion in the portfolio (PWT) for the different sectors of the USA. The threshold values θ_e and θ_p (as 2% of the coefficient of variations of EVC and PWT, respectively) would determine, whether the sector is central or not (EVC is 0 or 1), or whether the corresponding sector would appear in the optimal portfolio or not (PWT is 0 or 1). The labels for the different sectors are given in table 1. *Upper Right*: The Hamming distance D computed from the bit-strings EVC and PWT, against the different values of n (percentage) of the coefficient of variations of EVC and PWT, respectively, which determine the threshold values θ_e and θ_p . *Lower*: The Hamming distance D computed from the bit-strings EVC and PWT, against the different values of n , for the different countries, plotted as a 3D-bar.

3.3 Constructing the minimum risk portfolio

In this part, we study how the sectoral centralities influence the aggregate risk of a portfolio. For the purpose of simple exposition, we compute the benchmark model of Markowitz portfolio selection with the sectoral return data. Assuming rational investors with risk-aversion, the investors will minimize

$$w'\Sigma w - \Theta R'w, \quad (6)$$

with respect to the weight vector w , where Σ is the covariance matrix of the sectoral returns, R' is the expected return vector and Θ is a parameter which denotes the risk appetite of the investor. We set a short-selling constraint ($w_i \geq 0$) and Θ equals to zero for finding the minimal risk portfolio which will entail a convex combination of sectoral returns (the other extreme would lead to a corner solution).

Our main observation in this part is that the optimal weight vector, w^* , is negatively related to the eigenvector centralities, i.e., if a sector is very “central” in the return correlation network ρ , then it is less likely to appear in the optimal portfolio with the minimum risk (and no short selling). We demonstrate this in a naive way: we construct threshold values θ_e and θ_p , as a fixed percentage (say $n\%$ of the coefficient of variation (standard deviation/mean) for both the eigenvector centralities, as well as the minimum risk portfolio weights, respectively. These threshold values θ_e and θ_p would determine, respectively, whether the sector is central or not (i.e., 0 or 1), or whether the corresponding sector would appear in your optimal portfolio or not (i.e., 0 or 1). So, for the vector of sectors, we would have two strings of 0’s or 1’s corresponding to the centrality vector (EVC) and the optimal weight vector (PWT), respectively. The Hamming distance D between any two bit-strings of equal length, is the number of positions at which the corresponding bits are different. So, the Hamming distance between the two strings EVC and PWT would tell how significant the observation is for a particular country; higher the value of D , better the conformity. The sector which is central (i.e., 1) would not appear in your portfolio (i.e., 0), and so for any country the ideal finding would be that D is unity. The choice of the threshold(s), θ_e and θ_p , equaled by the percentage(s) (n) of the coefficient of variation(s) in the vectors EVC and PWT, would be important for determining the Hamming distance D between the strings for any country (see Fig. 6 (*Upper*)) for the USA. We can optimize the value of D against the percentage n , for all the countries, as shown in Fig. 6 (*Lower*). We found that $n = 2$, i.e. 2% was an optimal threshold value θ_e for most countries, which we then used to distinguish between the core and periphery sectors. Combined with the finding that core sectors in the return correlation network are bigger in size, the above finding implies that peripheral sectors contribute to lower risk of a diversified portfolio.

4 Summary and conclusion

In this paper, we have analyzed financial and economic data for 27 countries at the sector level. We show that the variation in the centrality in the return correlation matrix across sectoral indices,

can be explained by the size dispersion across the sectors. This finding indicates that financial fluctuations are mapped to the macroeconomic fundamentals. From the perspective of portfolio optimization, we show that the very big sectors that are also highly central in the return network, rarely appear in a risk-minimizing portfolio. Essentially, such sectors constitute the main drivers of the market-wide fluctuations. In summary, our study sheds light on: (a) the mapping between the joint evolution of the financial variables and the underlying macroeconomic fundamentals, and (b) extracting information about the individual influences on aggregate risk from sector-level, disaggregated time-series data.

Methodologically, we provide a way to extract the core-periphery structure of the correlation networks in a binary fashion. As a result, the generic rule of thumb we come up with is that size is an important causal factor even behind financial fluctuations. We attribute significant importance to this finding as it provides a way to exactly pin down the sectors, which are main drivers of financial fluctuations through the size effect. The way return series are constructed, the size differential of the prices across the sectoral indices, should disappear due to the normalization. The fact that the co-movements are still tied to the fundamentals is therefore intriguing. As our results suggest, the finding is considerably robust across countries. An illuminating exception is Greece showing an exact opposite relationship, which has been known to possess weak economic fundamentals along with severe crises in the financial markets in the recent times. In both periods, economically large (either in terms of market capitalization or revenue or employment) sectors in Greece are at the periphery of the return correlation networks, which constitute an inverted relationship between the economy and the financial networks.

We have also shown that the relative importance of the sectors may change significantly over time although some sectors like finance and industry are at the core of a significant fraction of countries. In general, our results indicate that the core may not be very stable. Possible reasons could be sectoral competition in terms of productivity and innovation and the resultant evolution [17]. The emergence of the core-periphery structure changes the complexity of the financial markets and has implications of the pricing of risk in the economy [18]. Our work indicates the potentials of using a binary characterization to reduce the computational burden by introducing proper identification of the country-specific core sectors, as opposed to considering the full network.

To conclude, we note that the recent applications of network theory in the macroeconomics literature has focused mostly on studying the dynamics of real economic quantities [19], whereas the relevant finance literature has focused on the dynamics of nominal quantities [20]. The present work may provide a linkage between the two. In other words, we make the point that the oft-quoted quips ‘too-big-to-fail’ and ‘too-interconnected-to-fail’ may not be as different as is currently thought of [21].

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Supplementary material

All detailed regression tables are provided below.

Table 2: Regression table: Dependent variable is the scaled centrality and the independent variable is the scaled market capitalization (2015-16). *** : significant at 1%, **: at 5%, *: at 10%.

Countries	β_0	Tstat	Pvalue	β_1	Tstat	Pvalue	Rsquare
Australia	0.0000 (0.3481)	0.0000	0.9999	0.2131 (0.3692)	0.5773	0.5817	0.0454
Belgium	0.0000 (0.3695)	0.0000	0.9999	0.2517 (0.3951)	0.6371	0.5475	0.0633
Canada	0.0000 (0.3018)	0.0000	0.9999	0.0758 (0.3153)	0.2404	0.8148	0.0057
Denmark	0.0000 (0.2703)	0.0000	0.9999	0.5918 (0.2849)	2.0767	0.0714*	0.3502
Finland	0.0000 (0.2246)	0.0000	0.9999	0.7425 (0.2368)	3.1353	0.0139**	0.5513
France	0.0000 (0.2523)	0.0000	0.9999	0.7003 (0.2394)	2.7751	0.0241**	0.4904
Germany	0.0000 (0.2544)	0.0000	0.9999	0.6516 (0.2681)	2.4299	0.0412**	0.4246
Greece	0.0000 (0.1617)	0.0000	0.9999	-0.8759 (0.1705)	-5.1368	0.0008***	0.7673
Hong Kong	0.0000 (0.3042)	0.0000	0.9999	0.4208 (0.3207)	1.3123	0.2257	0.1771
India	0.0000 (0.3329)	0.0000	0.9999	0.1219 (0.3509)	0.3474	0.7373	0.0149
Indonesia	0.0000 (0.232)	0.0000	0.9999	0.7221 (0.2445)	2.9524	0.0183**	0.5214
Japan	0.0000 (0.3239)	0.0000	0.9999	0.2588 (0.3415)	0.7579	0.4702	0.0670
Malaysia	0.0000 (0.2719)	0.0000	0.9999	0.5853 (0.2866)	2.0421	0.0754*	0.3426
Netherlands	0.0000 (0.3292)	0.0000	0.9999	0.3821 (0.3492)	1.0941	0.3100	0.1460
Norway	0.0000 (0.2992)	0.0000	0.9999	0.4516 (0.3154)	1.4316	0.1901	0.2039
Philippines	0.0000 (0.1552)	0.0000	0.9999	0.9537 (0.1736)	5.4929	0.0118**	0.9095
Portugal	0.0000 (0.3133)	0.0000	0.9999	0.5715 (0.3349)	1.7061	0.1388	0.3266

Qatar	0.0000 (0.3742)	0.0000	0.9999	0.5723 (0.41)	1.3959	0.2352	0.3275
Saudi Arabia	0.0000 (0.2669)	0.0000	0.9999	0.2807 (0.277)	1.0133	0.3309	0.0788
South Africa	0.0000 (0.3739)	0.0000	0.9999	-0.2033 (0.3997)	-0.5086	0.6291	0.0413
Spain	0.0000 (0.2684)	0.0000	0.9999	0.1531 (0.5705)	0.8057	0.1577	0.0234
Sri Lanka	0.0000 (0.267)	0.0000	0.9999	0.5423 (0.28)	1.9363	0.0848*	0.2940
Sweden	0.0000 (0.2852)	0.0000	0.9999	0.5995 (0.3025)	1.9818	0.0879*	0.3594
Switzerland	0.0000 (0.2831)	0.0000	0.9999	0.4543 (0.2969)	1.5302	0.1603	0.2064
Thailand	0.0000 (0.3152)	0.0000	0.9999	0.5643 (0.337)	1.6743	0.1450	0.3184
UK	0.0000 (0.3132)	0.0000	0.9999	0.3575 (0.3301)	1.0830	0.3103	0.1278
USA	0.0000 (0.2728)	0.0000	0.9999	0.5817 (0.2875)	2.0228	0.0777*	0.3384

Table 3: Regression table: Dependent variable is the scaled centrality and the independent variable is the scaled revenue (2015-16). *** : significant at 1%, **: at 5%, *: at 10%.

Countries	β_0	Tstat	Pvalue	β_1	Tstat	Pvalue	Rsquare
Australia	0.0000 (0.3144)	0.0000	0.9999	0.4704 (0.3335)	1.4106	0.2012	0.2213
Belgium	0.0000 (0.2247)	0.0000	0.9999	0.8084 (0.2402)	3.3644	0.0151**	0.6535
Canada	0.0000 (0.2916)	0.0000	0.9999	0.2689 (0.3045)	0.8830	0.3979	0.0723
Denmark	0.0000 (0.2837)	0.0000	0.9999	0.5333 (0.299)	1.7834	0.1123	0.2844
Finland	0.0000 (0.2988)	0.0000	0.9999	0.4542 (0.3149)	1.4422	0.1872	0.2063
France	0.0000 (0.236)	0.0000	0.9999	0.7104 (0.2487)	2.8557	0.0212**	0.5048
Germany	0.0000 (0.3203)	0.0000	0.9999	0.2964 (0.3376)	0.8778	0.4056	0.0878
Greece	0.0000 (0.3069)	0.0000	0.9999	-0.4029 (0.3235)	-1.2453	0.2482	0.1623
Hong Kong	0.0000 (0.2877)	0.0000	0.9999	0.5140 (0.3032)	1.6948	0.1285	0.2642
India	0.0000 (0.3158)	0.0000	0.9999	0.3368 (0.3329)	1.0117	0.3413	0.1134
Indonesia	0.0000 (0.233)	0.0000	0.9999	0.7193 (0.2456)	2.9286	0.0190**	0.5173
Japan	0.0000 (0.3137)	0.0000	0.9999	0.3531 (0.3307)	1.0678	0.3167	0.1247
Malaysia	0.0000 (0.2746)	0.0000	0.9999	0.5739 (0.2895)	1.9824	0.0827*	0.3294
Netherlands	0.0000 (0.3411)	0.0000	0.9999	0.2886 (0.3618)	0.7976	0.4512	0.0833
Norway	0.0000 (0.222)	0.0000	0.9999	0.7495 (0.234)	3.2031	0.0125**	0.5618
Philippines	0.0000 (0.4578)	0.0000	0.9999	0.4625 (0.5118)	0.9035	0.4328	0.2139
Portugal	0.0000 (0.2655)	0.0000	0.9999	0.7187 (0.2838)	2.5320	0.0445**	0.5165

Qatar	0.0000 (0.4536)	0.0000	0.9999	-0.1102 (0.4969)	-0.2219	0.8352	0.0121
Saudi Arabia	- -						
South Africa	0.0000 (0.3129)	0.0000	0.9999	0.5729 (0.3346)	1.7121	0.1377	0.3282
Spain	0.0000 (0.5099)	0.0000	0.9999	0.1577 (0.5701)	0.2767	0.7999	0.0248
Sri Lanka	0.0000 (0.243)	0.0000	0.9999	0.6442 (0.2549)	2.5267	0.0324**	0.4150
Sweden	0.0000 (0.2945)	0.0000	0.9999	0.5626 (0.3124)	1.8006	0.1147	0.3165
Switzerland	0.0000 (0.2646)	0.0000	0.9999	0.5537 (0.2775)	1.9952	0.0771*	0.3066
Thailand	0.0000 (0.3558)	0.0000	0.9999	0.3628 (0.3804)	0.9538	0.3770	0.1316
UK	0.0000 (0.3346)	0.0000	0.9999	-0.0688 (0.3527)	-0.1952	0.8500	0.0047
USA	0.0000 (0.2667)	0.0000	0.9999	0.6063 (0.2811)	2.1566	0.0631*	0.3676

Table 4: Regression table: Dependent variable is the scaled centrality and the independent variable is the scaled number of employees (2015-16). *** : significant at 1%, **: at 5%, *: at 10%.

Countries	β_0	Tstat	Pvalue	β_1	Tstat	Pvalue	Rsquare
Australia	0.0000 (0.3038)	0.0000	0.9999	0.5225 (0.3222)	1.6213	0.1489	0.2730
Belgium	0.0000 (0.2631)	0.0000	0.9999	0.7247 (0.2812)	2.5766	0.0419**	0.5252
Canada	0.0000 (0.2919)	0.0000	0.9999	0.2652 (0.3049)	0.8698	0.4048	0.0703
Denmark	0.0000 (0.3164)	0.0000	0.9999	0.3316 (0.3335)	0.9942	0.3492	0.1099
Finland	0.0000 (0.2762)	0.0000	0.9999	0.5671 (0.2912)	1.9474	0.0873*	0.3216
France	0.0000 (0.1525)	0.0000	0.9999	0.8905 (0.1608)	5.5374	0.0005***	0.7930
Germany	0.0000 (0.2836)	0.0000	0.9999	0.5336 (0.299)	1.7845	0.1121	0.2847
Greece	0.0000 (0.1481)	0.0000	0.9999	-0.8971 (0.1561)	-5.7451	0.0004***	0.8049
Hong Kong	0.0000 (0.2471)	0.0000	0.9999	0.6759 (0.2605)	2.5943	0.0318**	0.4569
India	0.0000 (0.3354)	0.0000	0.9999	0.0189 (0.3535)	0.0534	0.9588	0.0003
Indonesia	0.0000 (0.2816)	0.0000	0.9999	0.5428 (0.2969)	1.8283	0.1049	0.2947
Japan	0.0000 (0.292)	0.0000	0.9999	0.4919 (0.3078)	1.5982	0.1486	0.2420
Malaysia	0.0000 (0.2975)	0.0000	0.9999	0.4615 (0.3136)	1.4717	0.1792	0.2130
Netherlands	0.0000 (0.2279)	0.0000	0.9999	0.7686 (0.2417)	3.1794	0.0155	0.5908
Norway	0.0000 (0.2736)	0.0000	0.9999	0.5784 (0.2884)	2.0054	0.0798*	0.3345
Philippines	0.0000 (0.4688)	0.0000	0.9999	0.4191 (0.5241)	0.7996	0.4823	0.1756
Portugal	0.0000 (0.3207)	0.0000	0.9999	0.5425 (0.3429)	1.5820	0.1647	0.2943

Qatar	- -						
Saudi Arabia	- -						
South Africa	0.0000 (0.3768)	0.0000	0.9999	0.1614 (0.4028)	0.4008	0.7024	0.0260
Spain	0.0000 (0.483)	0.0000	0.9999	0.3537 (0.5400)	0.6550	0.5591	0.1251
Sri Lanka	0.0000 (0.1924)	0.0000	0.9999	0.7958 (0.2018)	3.9435	0.0033***	0.6334
Sweden	0.0000 (0.315)	0.0000	0.9999	0.4673 (0.3341)	1.3986	0.2046	0.2184
Switzerland	0.0000 (0.2719)	0.0000	0.9999	0.5177 (0.2851)	1.8154	0.1028	0.2680
Thailand	- -						
UK	0.0000 (0.255)	0.0000	0.9999	0.6495 (0.2688)	2.4165	0.0420**	0.4219
USA	0.0000 (0.2529)	0.0000	0.9999	0.6566 (0.2666)	2.4628	0.0391**	0.4312

Table 5: Regression table: Dependent variable is the scaled centrality and the independent variable is the scaled market capitalization (2008-09). *** : significant at 1%, **: at 5%, *: at 10%.

Countries	β_0	Tstat	Pvalue	β_1	Tstat	Pvalue	Rsquare
Australia	0.0000 (0.3507)	0.0000	0.9999	0.1770 (0.3719)	0.4759	0.6485	0.0313
Belgium	0.0000 (0.3791)	0.0000	0.9999	-0.1193 (0.4053)	-0.2943	0.7783	0.0142
Canada	0.0000 (0.3027)	0.0000	0.9999	0.0000 (0.3162)	0.0001	0.9998	0.0000
Denmark	0.0000 (0.3058)	0.0000	0.9999	0.4103 (0.3224)	1.2727	0.2388	0.1683
Finland	- -						
France	0.0000 (0.3074)	0.0000	0.9999	0.3995 (0.3241)	1.2329	0.2526	0.1596
Germany	0.0000 (0.2716)	0.0000	0.9999	0.5865 (0.2863)	2.0484	0.0746*	0.3440
Greece	0.0000 (0.3327)	0.0000	0.9999	0.1258 (0.3507)	0.3587	0.7290	0.0158
Hong Kong	0.0000 (0.3173)	0.0000	0.9999	0.3239 (0.3344)	0.9684	0.3611	0.1049
India	0.0000 (0.2756)	0.0000	0.9999	0.5696 (0.2905)	1.9605	0.0855*	0.3245
Indonesia	0.0000 (0.2925)	0.0000	0.9999	0.4891 (0.3083)	1.5861	0.1513	0.2392
Japan	0.0000 (0.334)	0.0000	0.9999	0.0915 (0.352)	0.2600	0.8013	0.0083
Malaysia	0.0000 (0.273)	0.0000	0.9999	0.5809 (0.2877)	2.0188	0.0782*	0.3375
Netherlands	0.0000 (0.3165)	0.0000	0.9999	0.4594 (0.3357)	1.3686	0.2134	0.2110
Norway	0.0000 (0.3016)	0.0000	0.9999	0.4369 (0.318)	1.3739	0.2067	0.1909
Philippines	0.0000 (0.4176)	0.0000	0.9999	0.5880 (0.4669)	1.2592	0.2970	0.3457
Portugal	0.0000 (0.3116)	0.0000	0.9999	0.5779 (0.3331)	1.7346	0.1334	0.3340

Qatar	0.0000 (0.3914)	0.0000	0.9999	0.5140 (0.4288)	1.1987	0.2967	0.2642
Saudi Arabia	0.0000 (0.2714)	0.0000	0.9999	0.2179 (0.2817)	0.7734	0.4542	0.0474
South Africa	0.0000 (0.3802)	0.0000	0.9999	-0.0932 (0.4064)	-0.2293	0.8262	0.0086
Spain	0.0000 (0.4885)	0.0000	0.9999	0.3238 (0.5462)	0.5928	0.5950	0.1048
Sri Lanka	0.0000 (0.301)	0.0000	0.9999	-0.2309 (0.3243)	-0.7120	0.4945	0.0533
Sweden	0.0000 (0.3435)	0.0000	0.9999	0.3643 (0.2658)	0.7297	0.4892	0.0706
Switzerland	0.0000 (0.3173)	0.0000	0.9999	-0.0532 (0.3328)	-0.1599	0.8764	0.0028
Thailand	0.0000 (0.3677)	0.0000	0.9999	0.2691 (0.3931)	0.6845	0.5191	0.0724
UK	0.0000 (0.3346)	0.0000	0.9999	0.0691 (0.3527)	0.1959	0.8495	0.0047
USA	0.0000 (0.3315)	0.0000	0.9999	0.1508 (0.3495)	0.4315	0.6774	0.0227

Table 6: Regression table: Dependent variable is the scaled centrality and the independent variable is the scaled revenue (2008-09). *** : significant at 1%, **: at 5%, *: at 10%.

Countries	β_0	Tstat	Pvalue	β_1	Tstat	Pvalue	Rsquare
Australia	0.0000 (0.335)	0.0000	0.9999	0.3408 (0.3553)	0.9592	0.3694	0.1161
Belgium	0.0000 (0.3676)	0.0000	0.9999	-0.2708 (0.3929)	-0.6891	0.5164	0.0733
Canada	0.0000 (0.2869)	0.0000	0.9999	0.3194 (0.2996)	1.0658	0.3115	0.1020
Denmark	0.0000 (0.2908)	0.0000	0.9999	0.4982 (0.3065)	1.6254	0.1427	0.2482
Finland	- -						
France	0.0000 (0.2457)	0.0000	0.9999	0.6805 (0.259)	2.6273	0.0303**	0.4631
Germany	0.0000 (0.2792)	0.0000	0.9999	0.5538 (0.2943)	1.8814	0.0966*	0.3067
Greece	0.0000 (0.3071)	0.0000	0.9999	-0.4015 (0.3237)	-1.2401	0.2500	0.1612
Hong Kong	0.0000 (0.2956)	0.0000	0.9999	0.4719 (0.3116)	1.5142	0.1684	0.2227
India	0.0000 (0.3022)	0.0000	0.9999	0.4333 (0.3186)	1.3601	0.2108	0.1878
Indonesia	0.0000 (0.2747)	0.0000	0.9999	0.5734 (0.2896)	1.9798	0.0830*	0.3288
Japan	0.0000 (0.3226)	0.0000	0.9999	0.2727 (0.3401)	0.8018	0.4458	0.0743
Malaysia	0.0000 (0.2758)	0.0000	0.9999	0.5687 (0.2908)	1.9555	0.0862*	0.3234
Netherlands	0.0000 (0.3406)	0.0000	0.9999	0.2934 (0.3613)	0.8122	0.4433	0.0861
Norway	0.0000 (0.2482)	0.0000	0.9999	0.6723 (0.2617)	2.5688	0.0331**	0.4520
Philippines	0.0000 (0.4791)	0.0000	0.9999	0.3728 (0.5357)	0.6959	0.5365	0.1389
Portugal	0.0000 (0.2975)	0.0000	0.9999	0.6268 (0.318)	1.9705	0.0962*	0.3928

Qatar	0.0000 (0.3915)	0.0000	0.9999	-0.5138 (0.4289)	-1.1979	0.2970	0.2640
Saudi Arabia	0.0000 (0.274)	0.0000	0.9999	0.1724 (0.2843)	0.6064	0.5555	0.0297
South Africa	0.0000 (0.3191)	0.0000	0.9999	0.5492 (0.3411)	1.6100	0.1585	0.3017
Spain	0.0000 (0.367)	0.0000	0.9999	0.7033 (0.4103)	1.7139	0.1850	0.4947
Sri Lanka	0.0000 (0.3167)	0.0000	0.9999	-0.0857 (0.3321)	-0.2579	0.8022	0.0073
Sweden	0.0000 (0.3071)	0.0000	0.9999	0.5071 (0.3257)	1.5566	0.1634	0.2571
Switzerland	0.0000 (0.3153)	0.0000	0.9999	0.1245 (0.3307)	0.3765	0.7152	0.0155
Thailand	0.0000 (0.3748)	0.0000	0.9999	0.1908 (0.4007)	0.4761	0.6507	0.0364
UK	0.0000 (0.3293)	0.0000	0.9999	0.1884 (0.3472)	0.5427	0.6020	0.0355
USA	0.0000 (0.3319)	0.0000	0.9999	0.1431 (0.3499)	0.4091	0.6931	0.0205

Table 7: Regression table: Dependent variable is the scaled centrality and the independent variable is the scaled number of employees (2008-09). *** : significant at 1%, **: at 5%, *: at 10%.

Countries	β_0	Tstat	Pvalue	β_1	Tstat	Pvalue	Rsquare
Australia	0.0000 (0.3369)	0.0000	0.9999	0.3251 (0.3574)	0.9095	0.3932	0.1056
Belgium	0.0000 (0.3802)	0.0000	0.9999	-0.0918 (0.4065)	-0.2259	0.8287	0.0084
Canada	0.0000 (0.2953)	0.0000	0.9999	0.2206 (0.3084)	0.7154	0.4907	0.0486
Denmark	0.0000 (0.3154)	0.0000	0.9999	0.3400 (0.3324)	1.0226	0.3364	0.1156
Finland	- -						
France	0.0000 (0.2558)	0.0000	0.9999	0.6465 (0.2697)	2.3971	0.0433**	0.4180
Germany	0.0000 (0.2916)	0.0000	0.9999	0.4939 (0.3074)	1.6066	0.1468	0.2439
Greece	0.0000 (0.3353)	0.0000	0.9999	-0.0177 (0.3534)	-0.0502	0.9611	0.0003
Hong Kong	0.0000 (0.2864)	0.0000	0.9999	0.5200 (0.3019)	1.7222	0.1233	0.2704
India	0.0000 (0.3088)	0.0000	0.9999	0.3903 (0.3255)	1.1991	0.2647	0.1523
Indonesia	0.0000 (0.2749)	0.0000	0.9999	0.5726 (0.2898)	1.9759	0.0835*	0.3279
Japan	0.0000 (0.2938)	0.0000	0.9999	0.4823 (0.3096)	1.5575	0.1579	0.2326
Malaysia	0.0000 (0.2835)	0.0000	0.9999	0.5341 (0.2988)	1.7870	0.1117	0.2853
Netherlands	0.0000 (0.3165)	0.0000	0.9999	0.4592 (0.3357)	1.3679	0.2136	0.2109
Norway	0.0000 (0.2467)	0.0000	0.9999	0.6772 (0.2601)	2.6034	0.0314**	0.4586
Philippines	0.0000 (0.4808)	0.0000	0.9999	0.3644 (0.5376)	0.6777	0.5465	0.1327
Portugal	0.0000 (0.329)	0.0000	0.9999	0.5074 (0.3517)	1.4425	0.1992	0.2575

Qatar	- -						
Saudi Arabia	- -						
South Africa	0.0000 (0.364)	0.0000	0.9999	0.3017 (0.3892)	0.7753	0.4675	0.0910
Spain	0.0000 (0.4049)	0.0000	0.9999	0.6205 (0.4527)	1.3707	0.2640	0.3851
Sri Lanka	0.0000 (0.2997)	0.0000	0.9999	0.3330 (0.3143)	1.0594	0.3170	0.1109
Sweden	0.0000 (0.3213)	0.0000	0.9999	0.4321 (0.3408)	1.2679	0.2453	0.1867
Switzerland	0.0000 (0.3083)	0.0000	0.9999	0.2419 (0.3234)	0.7481	0.4734	0.0585
Thailand	0.0000 (0.3618)	0.0000	0.9999	-0.3195 (0.3868)	-0.8259	0.4404	0.1020
UK	0.0000 (0.2444)	0.0000	0.9999	0.6847 (0.2576)	2.6571	0.0289**	0.4688
USA	0.0000 (0.2776)	0.0000	0.9999	0.5610 (0.2926)	1.9171	0.0915*	0.3148